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A CRITIC-Weighted Fuzzy-TOPSIS and Machine Learning Framework for Evaluating Corporate Governance Efficiency: Evidence from Construction Materials Manufacturing in Uzbekistan

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Abstract

We develop a hybrid framework integrating CRITIC objective weighting, Fuzzy-TOPSIS governance ranking, and machine learning to evaluate corporate governance efficiency in Uzbekistan's construction materials sector. Twenty domain experts rated eight manufacturers on ten governance indicators using a 7-point Likert scale, yielding 160 observations. CRITIC assigned the highest weights to strategic planning (0.130) and risk management (0.115). Four ML models—Random Forest, XGBoost, SVR, and ANN—trained under leave-one-enterprise-out cross-validation to predict actual Return on Assets from governance indicators. The governance ranking correlated negatively with financial performance (Spearman $\rho = -0.24$), revealing that expert perceptions bear little relation to profitability. SHAP analysis showed that stakeholder relations—employee and government relations—dominated the association with ROA, while structural governance dimensions contributed least. The findings document a governance paradox: the dimensions that best differentiate enterprises in expert perception are not those most closely tied to profit, and relational governance outweighs structural governance in its association with financial performance.

Keywords: corporate governance; construction materials manufacturing; CRITIC; Fuzzy-TOPSIS; machine learning; SHAP

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1 Introduction

Corporate governance—the system of rules, practices, and processes by which an enterprise is directed and controlled—has occupied a central place in the finance literature since the foundational contributions of [24] and [4]. Good governance aligns the interests of management, shareholders, and other stakeholders while promoting transparency, accountability, and long-term value creation [21]. These properties matter everywhere, but they matter disproportionately in emerging economies, where institutional frameworks are still maturing and capital markets are thinner: governance quality shapes investor confidence, determines access to external finance, and can alter the trajectory of entire industrial sectors [10; 19].

Uzbekistan's construction materials manufacturing sector illustrates the point. Rapid modernization and infrastructure investment have driven growth in output and enterprise formation, yet the development of governance institutions has not kept pace. Many firms in the sector—cement, brick, reinforced concrete, and inert materials producers—continue to operate under concentrated ownership, limited board independence, weak internal controls, and scant financial disclosure [28]. The costs are tangible: constrained access to capital, lower operational efficiency, and elevated exposure to mismanagement.

No widely accepted methodology exists for systematically evaluating governance efficiency in this context. The available toolkit is broad, but each approach has recognized limitations. Scorecard-based indices such as the G-Index [15] rely on binary indicators and flatten the multidimensional character of governance quality. Econometric methods require large panel datasets that are simply unavailable where corporate disclosure is limited. Multi-criteria decision-making (MCDM) techniques—the Analytic Hierarchy Process [23], TOPSIS [16], Data Envelopment Analysis [5]—synthesize multiple dimensions into a ranking, but the rankings are static and cannot accommodate non-linear relationships among governance factors.

Machine learning (ML) offers a way forward. ML algorithms can detect complex, non-linear patterns in governance data, generate predictive rather than purely descriptive assessments, and identify which governance factors carry the most weight through feature importance analysis [3; 7]. Yet ML has barely been applied to corporate governance evaluation, least of all in data-scarce emerging-economy settings.

We address this gap by developing and empirically testing a hybrid framework that joins MCDM and ML approaches. The framework proceeds in three stages: (1) the CRITIC method derives objective indicator weights from the data, and Fuzzy-TOPSIS generates a baseline governance ranking; (2) four ML models—Random Forest, XGBoost, Support Vector Regression, and an Artificial Neural Network—are trained to predict actual Return on Assets (ROA) from the governance indicators; and (3) SHAP analysis reveals which governance factors are most closely associated with real enterprise profitability. The ML target is not a formula-derived governance score but actual ROA computed from official financial records, establishing a direct, verifiable link between governance quality and economic outcomes.

The paper makes three contributions. It provides, to our knowledge, the first dedicated governance evaluation framework calibrated to Uzbekistan's construction materials industry—a sector with no prior empirical coverage. It documents a systematic disconnect between expert-perceived governance quality and actual financial performance, showing that

governance perceptions and profitability do not move together in this transitional economy. And it uses SHAP-based feature importance to identify which governance dimensions track financial outcomes most closely, uncovering a striking pattern: relational factors (stakeholder relations) outweigh structural ones (board composition, strategic planning) in their association with enterprise profitability, a finding that reorders the reform priorities implied by conventional governance frameworks.

The paper proceeds as follows. Section 2 reviews the relevant literature. Section 3 presents the hybrid framework. Section 4 describes data collection and the survey instrument. Section 5 reports the empirical results, Section 6 discusses their implications, and Section 7 concludes.

2 Literature review

2.1 Corporate governance in emerging economies

The theoretical foundations of corporate governance research—agency theory [17] and the survey by [24]—were built in advanced economies with well-functioning legal systems and liquid capital markets. Extending this research to emerging economies raised a different set of problems: weaker investor protection [19], concentrated and frequently state-linked ownership [9], underdeveloped external governance mechanisms, and institutional voids that force firms to rely on informal substitutes for formal governance arrangements [18].

[10] surveyed the emerging-market governance literature and identified ownership concentration, related-party transactions, and ineffective boards as recurring weaknesses. Region-specific studies have since examined East Asia [14], Latin America [8], and Sub-Saharan Africa [26]. Central Asian economies, including Uzbekistan, remain conspicuously absent from this body of work, despite their distinctive transitional characteristics: post-Soviet institutional legacies, rapid privatization, and regulatory environments that are still taking shape.

What limited evidence exists for Uzbekistan suggests governance challenges typical of transitional economies but refracted through sector-specific conditions. The construction materials manufacturing sector mixes state-owned enterprises undergoing corporatization with private firms that emerged from privatization carrying governance structures never designed for market-economy accountability.

2.2 Corporate governance evaluation methods

Governance evaluation has been approached through several methodological traditions. Scorecard-based indices—the G-Index [15], the E-Index [2]—count the presence or absence of specific provisions. They are simple and comparable across firms, but they weight all provisions equally and cannot capture the multidimensional, context-dependent character of governance quality.

MCDM methods address some of these shortcomings. The Analytic Hierarchy Process (AHP) of [23] decomposes an evaluation problem into hierarchical criteria and derives weights through pairwise comparisons. TOPSIS [16] ranks alternatives by their geometric distance

to a positive ideal and from a negative ideal solution. Data Envelopment Analysis [5] frames governance efficiency as an input-output ratio estimated by linear programming.

Each method, however, has well-known drawbacks. AHP's pairwise comparisons grow quadratically with the number of criteria, imposing a heavy cognitive burden and raising consistency concerns. Standard TOPSIS operates on crisp values and cannot represent the inherent vagueness of expert judgment. DEA requires clearly defined inputs and outputs that are seldom unambiguous in governance settings.

Objective weighting methods sidestep the need for subjective expert comparisons altogether. The CRITIC method [13] derives weights from the contrast intensity and conflicting character of the evaluation data itself—criteria that vary more across alternatives and correlate less with one another receive higher weight. This purely data-driven approach is attractive when expert availability is limited or when minimizing subjective bias is a priority.

[6] extended TOPSIS to fuzzy environments, enabling it to accommodate the linguistic imprecision inherent in expert assessments. Pairing Fuzzy-TOPSIS with CRITIC-derived weights yields a governance evaluation that is both fully data-driven and capable of handling rating uncertainty, without requiring pairwise comparisons.

2.3 Machine learning in corporate governance research

Machine learning has entered the governance literature only recently, but the trajectory is steep. Early applications targeted governance-related outcomes—earnings management [11], financial distress [1], fraud detection [27]—and showed that ML models could pick up non-linear patterns that traditional regressions missed.

More recent work has turned ML toward governance quality assessment itself. Random Forests [3] have been used to classify firms into governance quality tiers and to rank governance predictors by feature importance. XGBoost [7] has performed well on the structured, tabular datasets typical of governance research. Support Vector Machines [25] and neural networks have also been applied, though their advantage over tree-based methods is less consistent when datasets are small and features heterogeneous.

A key design choice is the target variable. Many studies predict governance scores derived from MCDM methods, but this is circular: the model learns to replicate a formula rather than to discover genuine governance-performance relationships. Using actual financial performance—ROA, Return on Equity, Tobin's Q—as the target avoids this circularity and grounds the analysis in real economic outcomes.

The interpretability gap in ML predictions has been largely closed by SHAP (SHapley Additive exPlanations) [20]. Rooted in cooperative game theory, SHAP values provide locally accurate, consistent feature attributions. They reveal not only which governance factors matter most for financial performance but also how each factor's marginal contribution varies across individual enterprises—exactly the kind of granularity that governance reform requires.

2.4 Research gap and contributions

Three gaps emerge from this review. Corporate governance in Central Asian economies—Uzbekistan's industrial sectors in particular—has received virtually no empirical attention.

Existing evaluation frameworks have not linked expert-assessed governance quality to real financial outcomes using ML methods; most use MCDM-derived scores as ML targets, creating the circularity noted above. And the construction materials manufacturing sector, despite its economic weight in developing countries, has not been the subject of dedicated governance evaluation research.

The present paper addresses all three gaps through an integrated CRITIC–Fuzzy-TOPSIS–ML framework. CRITIC-derived objective weights feed into a Fuzzy-TOPSIS baseline ranking; ML models are trained to predict real ROA from governance indicators; and SHAP analysis provides interpretability—all without the circularity of predicting formula-derived scores.

3 Methodology

The framework proceeds in three stages, summarized in Fig. 1: (1) objective criteria weighting via CRITIC and baseline governance ranking via Fuzzy-TOPSIS; (2) ML-based prediction of actual financial performance from governance indicators; and (3) SHAP feature importance analysis to identify which governance dimensions track profitability most closely.

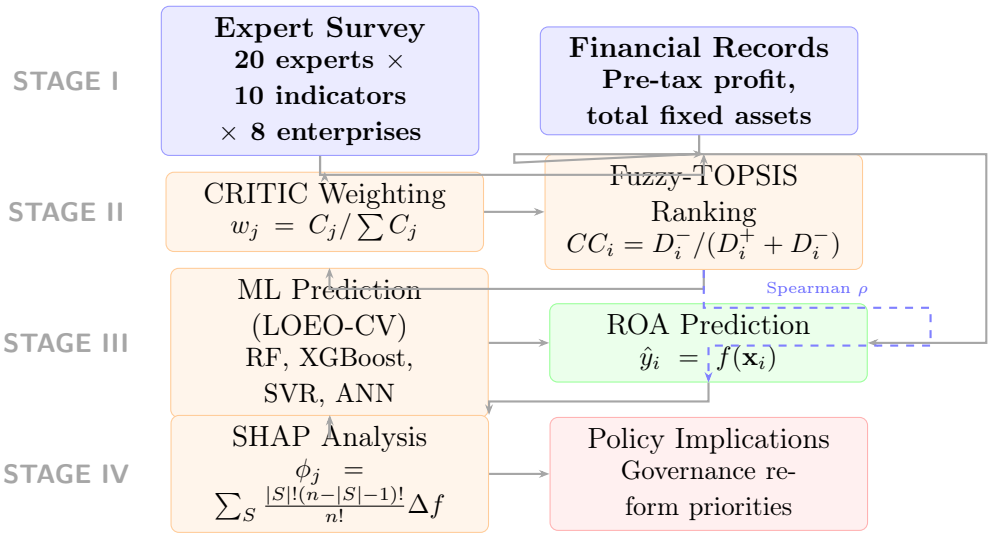


Figure 1: Overview of the proposed hybrid governance evaluation framework. Stage I collects primary survey data and financial records. Stage II applies CRITIC for objective weighting and Fuzzy-TOPSIS for governance ranking. Stage III trains ML models under leave-one-enterprise-out cross-validation to predict ROA. Stage IV uses SHAP to identify governance dimensions most closely associated with financial performance.

3.1 Governance evaluation criteria system

Drawing on the governance literature [24; 21; 10] and consultation with domain experts, we constructed a criteria system comprising five dimensions and ten indicators (two per dimension), summarized in Table 1. We deliberately limited the system to ten indicators

to reduce respondent burden and improve data quality; a concise, well-targeted instrument tends to yield more reliable assessments than an exhaustive one that induces fatigue [12].

Table 1: Corporate governance evaluation criteria system.

Dimension	**Code**	**Indicator**
D1: Board structure and leadership	C1.1	Board composition adequacy and member qualifications
	C1.2	Proportion and activity level of independent board members
D2: Financial transparency and accountability	C2.1	Completeness, accuracy, and reliability of financial reports
	C2.2	Independence and effectiveness of audit services
D3: Strategic management	C3.1	Level and quality of strategic planning
	C3.2	Innovation activity and investment in new technologies
D4: Internal control and risk management	C4.1	Existence and effective functioning of internal audit system
	C4.2	Mechanisms for risk identification, analysis, and management
D5: Stakeholder relations	C5.1	Quality of employee relations and motivation system
	C5.2	Constructive relations with government and regulatory authorities

3.2 CRITIC method for objective weighting

The CRITIC method [13] derives objective criteria weights from the contrast intensity and conflicting character of the evaluation data. Because the weights are determined entirely by the statistical structure of the decision matrix, CRITIC avoids the inconsistencies and cognitive biases that can arise from subjective pairwise comparisons.

Given a decision matrix $X = [x_{ij}]_{m\times n}$ with m alternatives (enterprise-expert observations) and n criteria (governance indicators):

Step 1. Normalize the decision matrix using min-max normalization:

$$r_{ij} = \frac{x_{ij} - \min_i(x_{ij})}{\max_i(x_{ij}) - \min_i(x_{ij})} \tag{1}$$

Step 2. Compute the standard deviation σ_j for each criterion j, which captures the contrast intensity—the degree of differentiation among alternatives on that criterion:

$$\sigma_j = \sqrt{\frac{1}{m-1}\sum_{i=1}^{m}(r_{ij} - \bar{r}_j)^2} \tag{2}$$

Step 3. Compute the Pearson correlation coefficient ρ_{jk} between each pair of criteria j and k:

$$\rho_{jk} = \frac{\sum_{i=1}^{m}(r_{ij} - \bar{r}_j)(r_{ik} - \bar{r}_k)}{\sqrt{\sum_{i=1}^{m}(r_{ij} - \bar{r}_j)^2 \sum_{i=1}^{m}(r_{ik} - \bar{r}_k)^2}} \tag{3}$$

A high positive correlation between criteria j and k indicates redundancy; the term $(1-\rho_{jk})$ in the next step penalizes such overlap.

Step 4. Calculate the information content C_j for each criterion:

$$C_j = \sigma_j \sum_{k=1}^{n} (1 - \rho_{jk}) \tag{4}$$

The formula rewards two properties simultaneously: criteria with more variability (higher σ_j) and less redundancy with other criteria (higher conflicting character) receive larger weights, reflecting their greater informational contribution.

Step 5. Derive the objective weights:

$$w_j = \frac{C_j}{\sum_{j=1}^{n} C_j} \tag{5}$$

3.3 Fuzzy-TOPSIS for baseline governance evaluation

The Fuzzy-TOPSIS method [6] extends the classical TOPSIS framework [16] to handle fuzzy evaluation data. Given m alternatives (enterprises) evaluated on n criteria with CRITIC-derived weights w_j:

Step 1. Construct the fuzzy decision matrix $\tilde{D} = [\tilde{x}_{ij}]_{m \times n}$, where each element $\tilde{x}_{ij}$ is the aggregated fuzzy rating of enterprise i on criterion j.

For aggregating individual expert ratings, the Likert-scale evaluations are converted to triangular fuzzy numbers (TFNs) as shown in Supplementary Table S1, and the aggregated fuzzy rating is:

$$\tilde{x}_{ij} = \frac{1}{K_i} \sum_{k=1}^{K_i} \tilde{x}_{ij}^{(k)} \tag{6}$$

where K_i is the number of experts who evaluated enterprise i (which may vary across enterprises since experts are permitted to leave cells blank for enterprises they are unfamiliar with).

A triangular fuzzy number is defined as a triplet $\tilde{a} = (l, m, u)$, where l, m, and u represent the lower bound, modal value, and upper bound, respectively, with $l \leq m \leq u$. The basic arithmetic operations for TFNs $\tilde{a}_1 = (l_1, m_1, u_1)$ and $\tilde{a}_2 = (l_2, m_2, u_2)$ are:

$$\tilde{a}_1 \oplus \tilde{a}_2 = (l_1 + l_2,\ m_1 + m_2,\ u_1 + u_2) \tag{7}$$

$$\tilde{a}_1 \otimes \tilde{a}_2 = (l_1 \cdot l_2,\ m_1 \cdot m_2,\ u_1 \cdot u_2) \tag{8}$$

$$\tilde{a}_1^{-1} = (1/u_1,\ 1/m_1,\ 1/l_1) \tag{9}$$

Step 2. Normalize the fuzzy decision matrix. Since all governance criteria are benefit-type (higher is better):

$$\tilde{r}_{ij} = \left(\frac{l_{ij}}{u_j^+},\ \frac{m_{ij}}{u_j^+},\ \frac{u_{ij}}{u_j^+} \right) \tag{10}$$

where $u_j^+ = \max_i(u_{ij})$.

Step 3. Compute the weighted normalized fuzzy decision matrix:

$$\tilde{v}_{ij} = w_j \otimes \tilde{r}_{ij} \tag{11}$$

Step 4. Define the fuzzy positive ideal solution (FPIS) A^+ and fuzzy negative ideal solution (FNIS) A^-:

$$A^+ = (\tilde{v}_1^+, \tilde{v}_2^+, \ldots, \tilde{v}_n^+), \quad \tilde{v}_j^+ = \max_i(\tilde{v}_{ij}) \tag{12}$$

$$A^- = (\tilde{v}_1^-, \tilde{v}_2^-, \ldots, \tilde{v}_n^-), \quad \tilde{v}_j^- = \min_i(\tilde{v}_{ij}) \tag{13}$$

Step 5. Calculate the distance of each alternative from FPIS and FNIS using the vertex method:

$$d(\tilde{a}, \tilde{b}) = \sqrt{\frac{1}{3}\left[(l_a - l_b)^2 + (m_a - m_b)^2 + (u_a - u_b)^2\right]} \tag{14}$$

$$D_i^+ = \sum_{j=1}^{n} d(\tilde{v}_{ij}, \tilde{v}_j^+) \tag{15}$$

$$D_i^- = \sum_{j=1}^{n} d(\tilde{v}_{ij}, \tilde{v}_j^-) \tag{16}$$

Step 6. Compute the closeness coefficient for each enterprise:

$$CC_i = \frac{D_i^-}{D_i^+ + D_i^-}, \quad 0 \le CC_i \le 1 \tag{17}$$

A higher CC_i indicates that enterprise i is closer to the ideal governance profile. The closeness coefficients produce a baseline governance ranking that serves as a reference for comparison with the ML-based predictions. The CC_i values are *not* used as the ML target variable; instead, real financial performance (ROA) serves as the prediction target, as described in Section 3.4.

3.4 Machine learning models for governance-performance prediction

The key design decision is the choice of target variable. Rather than predicting a governance score derived from the MCDM stage, we train ML models to predict actual Return on Assets (ROA), computed from official enterprise financial records:

$$\text{ROA}_i = \frac{\text{Pre-tax Profit}_i}{\text{Total Fixed Assets}_i} \times 100\% \tag{18}$$

The input features are the ten governance indicators (C1.1 through C5.2) as rated by each expert for each enterprise on the 1–7 Likert scale. Since each expert evaluates multiple enterprises, and multiple experts evaluate each enterprise, the dataset consists of individual expert-enterprise observations $(\mathbf{x}_{ij}, \text{ROA}_j)$, where $\mathbf{x}_{ij} \in \mathbb{R}^{10}$ is the governance indicator vector assigned by expert i to enterprise j, and ROA_j is the real financial performance of enterprise j. Before training, features are standardized to zero mean and unit variance:

$$z_{ij}^{(p)} = \frac{x_{ij}^{(p)} - \bar{x}^{(p)}}{s^{(p)}}, \quad p = 1, \ldots, 10 \tag{19}$$

where $\bar{x}^{(p)}$ and $s^{(p)}$ are the training-set mean and standard deviation of indicator p. Standardization parameters are fitted on the training fold and applied to the held-out fold to prevent information leakage.

Four ML models are trained:

Random Forest (RF). An ensemble method that constructs B decision trees on bootstrapped samples and averages their predictions [3]:

$$\hat{y}_{\mathrm{RF}}(\mathbf{x}) = \frac{1}{B}\sum_{b=1}^{B} T_b(\mathbf{x}) \tag{20}$$

where $T_b(\mathbf{x})$ is the prediction of the b-th tree. At each split, a random subset of $\lfloor\sqrt{n}\rfloor$ features is considered, decorrelating the individual trees and reducing variance.

XGBoost. An optimized gradient-boosted decision tree algorithm that builds M trees sequentially, with each tree fitted to the negative gradient of a regularized loss function [7]:

$$\hat{y}^{(t)}(\mathbf{x}) = \hat{y}^{(t-1)}(\mathbf{x}) + \eta\, h_t(\mathbf{x}) \tag{21}$$

where η is the learning rate and h_t minimizes the second-order Taylor expansion of the loss:

$$\mathcal{L}^{(t)} \approx \sum_{i=1}^{n}\left[g_i\, h_t(\mathbf{x}_i) + \tfrac{1}{2}\, h_i\, h_t^2(\mathbf{x}_i)\right] + \Omega(h_t) \tag{22}$$

with $g_i = \partial\ell/\partial\hat{y}^{(t-1)}$ and $h_i = \partial^2\ell/\partial(\hat{y}^{(t-1)})^2$ denoting the first- and second-order gradients, and $\Omega(h_t) = \gamma T + \frac{1}{2}\lambda\|\mathbf{w}\|^2$ penalizing tree complexity.

Support Vector Regression (SVR). SVR solves the ε-insensitive optimization problem [25]:

$$\min_{\mathbf{w},b,\boldsymbol{\xi}} \ \frac{1}{2}\|\mathbf{w}\|^2 + C\sum_{i=1}^{n}(\xi_i + \xi_i^*) \quad \text{s.t. } |y_i - \mathbf{w}^\top\phi(\mathbf{x}_i) - b| \le \varepsilon + \xi_i + \xi_i^* \tag{23}$$

where $\phi(\cdot)$ maps input features into a high-dimensional space via the radial basis function (RBF) kernel $K(\mathbf{x}_i, \mathbf{x}_j) = \exp(-\gamma\|\mathbf{x}_i - \mathbf{x}_j\|^2)$, C is the regularization parameter, and ε defines the margin of tolerance.

Artificial Neural Network (ANN). A multilayer perceptron that computes a forward pass through L hidden layers [22]:

$$\mathbf{h}^{(l)} = \sigma\big(\mathbf{W}^{(l)}\mathbf{h}^{(l-1)} + \mathbf{b}^{(l)}\big), \quad l = 1, \ldots, L \tag{24}$$

where $\sigma(\cdot) = \max(0, \cdot)$ is the ReLU activation, and the output layer produces the scalar prediction $\hat{y} = \mathbf{w}^{(L+1)\top}\mathbf{h}^{(L)} + b^{(L+1)}$. Parameters are optimized via backpropagation using the Adam optimizer, which adapts per-parameter learning rates using first- and second-moment estimates of the gradients.

3.5 SHAP analysis for model interpretability

We use SHAP (SHapley Additive exPlanations) analysis [20] to interpret the ML predictions and identify which governance factors are most closely tied to financial performance. SHAP values are grounded in cooperative game theory and satisfy three desirable properties: local accuracy, missingness, and consistency.

For a prediction $f(x)$, the SHAP value ϕ_j for feature j represents its marginal contribution:

$$f(x) = \phi_0 + \sum_{j=1}^{n} \phi_j \tag{25}$$

where ϕ_0 is the base value (mean prediction) and ϕ_j quantifies how much feature j pushes the prediction above or below the base value for a given observation.

The SHAP value for feature j is computed as the weighted average of its marginal contributions across all possible feature coalitions:

$$\phi_j = \sum_{S \subseteq N \setminus \{j\}} \frac{|S|!\,(|N| - |S| - 1)!}{|N|!} \left[f(S \cup \{j\}) - f(S) \right] \tag{26}$$

where N is the full set of features and S is a subset excluding feature j.

For tree-based models (RF and XGBoost), TreeSHAP provides exact SHAP values in polynomial time. The resulting SHAP summary plots and dependence plots reveal not only which governance dimensions matter most for financial performance but also the direction and magnitude of each factor's effect across different enterprises.

3.6 Model evaluation metrics

The predictive performance of the ML models is evaluated using four metrics:

$$\text{MAE} = \frac{1}{n} \sum_{i=1}^{n} |y_i - \hat{y}_i| \tag{27}$$

$$\text{RMSE} = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (y_i - \hat{y}_i)^2} \tag{28}$$

$$R^2 = 1 - \frac{\sum_{i=1}^{n} (y_i - \hat{y}_i)^2}{\sum_{i=1}^{n} (y_i - \bar{y})^2} \tag{29}$$

$$\text{MAPE} = \frac{1}{n} \sum_{i=1}^{n} \left| \frac{y_i - \hat{y}_i}{y_i} \right| \times 100\% \tag{30}$$

where y_i is the actual ROA, $\hat{y}_i$ is the predicted ROA, and $\bar{y}$ is the mean of actual ROA values.

Leave-one-enterprise-out (LOEO) cross-validation is performed to obtain unbiased estimates of model performance. In each fold, all observations from one enterprise are held out for testing while the model is trained on the remaining seven enterprises, ensuring that no

enterprise appears in both training and test sets. This group-based cross-validation design prevents data leakage that would arise from standard k-fold splitting, where different experts' ratings of the same enterprise could appear in both sets. The enterprise-level predicted ROA is computed as the average of individual predictions across all 20 experts for that enterprise:

$$\widehat{\mathrm{ROA}}_j = \frac{1}{K} \sum_{k=1}^{K} f(\mathbf{x}_{kj}) \tag{31}$$

where $K = 20$ is the number of experts and $f(\mathbf{x}_{kj})$ is the model's prediction for expert k's rating vector of enterprise j.

The Fuzzy-TOPSIS governance ranking is compared with the ML-derived and actual ROA rankings through Spearman's rank correlation coefficient:

$$\rho_s = 1 - \frac{6 \sum_{i=1}^{m} d_i^2}{m(m^2 - 1)} \tag{32}$$

where d_i is the difference between the ranks assigned to enterprise i by the two rankings and m is the number of enterprises. Statistical significance is assessed at the $\alpha = 0.05$ level.

4 Data collection and survey design

4.1 Survey instrument

Primary data were collected through a structured questionnaire administered to domain experts with direct knowledge of governance practices in Uzbekistan's construction materials manufacturing sector. The instrument was kept short to maximize response rates and data quality, and consists of two sections:

- **Section 1** (2 items): Respondent profile, including current position and years of experience in the construction materials sector.
- **Section 2** (matrix format): Assessment of corporate governance practices across eight specific enterprises on ten governance indicators using a 7-point Likert scale (1 = very poor to 7 = very good). The matrix format presents all eight enterprises as columns and all ten indicators as rows, enabling systematic cross-enterprise comparison. Respondents were instructed to leave cells blank for enterprises with which they lacked sufficient familiarity.

The questionnaire was administered in the Uzbek language. A boxed anonymity notice assured respondents that enterprise names would be anonymized in the published research (coded as E1 through E8 rather than by name) and that individual responses would not be traceable to any respondent.

4.2 Evaluated enterprises

Eight major construction materials manufacturing enterprises in Uzbekistan were selected for evaluation based on their market significance and representation of the sector's geographic and ownership diversity (Supplementary Table S2).

The sample includes six cement producers and two glass/quartz manufacturers, spanning five regions and representing both joint-stock companies and limited liability companies. This composition captures the structural diversity of the sector.

4.3 Financial performance data

Financial performance data were drawn from official enterprise records for the period 2019–2021. ROA was computed for each enterprise as the ratio of pre-tax profit to total fixed assets. Using real financial data as the ML target—rather than subjective ratings or MCDM-derived scores—grounds the analysis in verifiable economic outcomes.

4.4 Sample characteristics

A total of 20 domain experts participated in the survey, exceeding the initial target of 10–15 respondents. All 20 respondents provided complete evaluations for all eight enterprises on all ten indicators, yielding $20 \times 8 = 160$ expert-enterprise observations with no missing data. The respondent profile is summarized in Supplementary Table S3.

The respondent pool spans a range of seniority levels and professional backgrounds. Three-quarters had five or more years of sectoral experience, and 60% held senior positions (directors, financial officers, or department heads), so the evaluations rest on substantial professional familiarity with the assessed enterprises.

Supplementary Table S4 reports the financial performance data used as the machine learning target variable. ROA values were computed from 2021 official records of pre-tax profit and total fixed assets.

ROA values range from 17.1% (E3) to 37.1% (E2), reflecting substantial variation in financial performance across the sector. The ROA for E8 was obtained from published industry sources.

Internal consistency of the survey instrument was assessed via Cronbach's α:

$$\alpha = \frac{n}{n-1}\left(1 - \frac{\sum_{p=1}^{n} \sigma_p^2}{\sigma_{\text{total}}^2}\right) \tag{33}$$

where n is the number of indicators, σ_p^2 is the variance of indicator p across respondents, and σ_{total}^2 is the variance of the total score. Because the governance indicators span structurally heterogeneous dimensions and the eight enterprises differ markedly in size and ownership, the resulting α values are expected to be moderate; the design deliberately measures a broad governance construct rather than a homogeneous unidimensional trait.

5 Results

We report the results of the three-stage analysis in turn: CRITIC weighting and Fuzzy-TOPSIS governance ranking, ML model performance and ranking comparison, and SHAP feature importance.

5.1 Aggregated decision matrix

Expert evaluations were aggregated by computing the arithmetic mean of all 20 experts' ratings for each enterprise-indicator pair. Supplementary Table S5 presents the resulting 8×10 decision matrix. Mean scores ranged from 3.00 (E2 on C5.2, government relations) to 4.95 (E8 on C1.2, independent board members), with an overall average of 3.96, indicating that most governance dimensions were perceived as slightly below average across the sector.

5.2 CRITIC weights

The CRITIC method produced objective weights based on the contrast intensity and inter-criteria correlations of the aggregated decision matrix. Supplementary Table S6 reports the standard deviation, information content, and resulting weight for each governance indicator.

Strategic planning (C3.1) received the highest weight (0.130), followed by risk management (C4.2, 0.115) and audit independence (C2.2, 0.106). These three indicators combine high cross-enterprise variability with low intercriteria correlation, giving them the greatest discriminatory power. At the other end, employee relations (C5.1, 0.080) and innovation investment (C3.2, 0.086) showed relatively little variation across enterprises, suggesting that experts perceived these dimensions similarly across the sector. The weight distribution is displayed in Fig. 2.

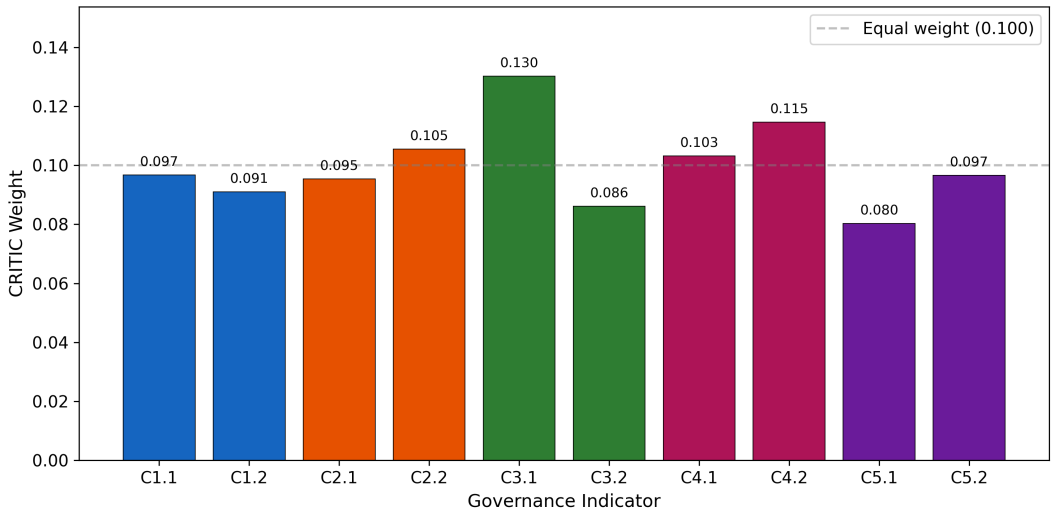


Figure 2: CRITIC objective weights for the ten governance indicators. Colors denote governance dimensions: D1 (blue), D2 (orange), D3 (green), D4 (pink), D5 (purple). The dashed line indicates equal weighting (0.100).

5.3 Fuzzy-TOPSIS results

Expert Likert ratings were converted to triangular fuzzy numbers, and the CRITIC-weighted Fuzzy-TOPSIS procedure was applied to compute closeness coefficients and enterprise rankings. Table 2 presents the distances to the fuzzy positive and negative ideal solutions, the resulting closeness coefficients, and the governance ranking.

Table 2: Fuzzy-TOPSIS governance ranking results.

Enterprise	D_i^+	D_i^-	CC_i	**TOPSIS Rank**	**Actual ROA Rank**
E1	0.0801	0.1268	0.6128	1	7
E4	0.0811	0.1261	0.6086	2	3
E5	0.0855	0.1231	0.5900	3	2
E6	0.0979	0.1088	0.5265	4	6
E8	0.1020	0.1052	0.5077	5	5
E3	0.1132	0.0936	0.4527	6	8
E7	0.1259	0.0805	0.3899	7	4
E2	0.1370	0.0697	0.3372	8	1

E1 ranked highest in perceived governance quality ($CC_1 = 0.613$), followed by E4 ($CC_4 = 0.609$) and E5 ($CC_5 = 0.590$). E2 ranked last ($CC_2 = 0.337$). The governance ranking diverges substantially from the actual ROA ranking: E2, ranked last in governance perception, has the highest ROA (37.1%), while E1, ranked first in governance perception, has a below-average ROA (17.4%). Supplementary Fig. S1 displays the closeness coefficients in descending order.

5.4 Machine learning model performance

Four ML models were trained on the 160-observation dataset (20 experts $\times$ 8 enterprises) and evaluated using leave-one-enterprise-out cross-validation, in which all observations from one enterprise were held out in each fold. Table 3 reports the enterprise-level performance metrics.

Table 3: Machine learning model performance under leave-one-enterprise-out cross-validation.

Model	**MAE (%)**	**RMSE (%)**	R^2	**MAPE (%)**
ANN	4.79	6.40	-0.181	19.9
SVR	4.71	6.58	-0.251	19.3
XGBoost	4.79	6.70	-0.296	20.4
Random Forest	4.80	6.76	-0.317	20.3

Every model returned a negative R^2, meaning that none predicted enterprise-level ROA better than the sample mean. The ANN came closest ($R^2 = -0.181$, MAE = 4.79%), but the differences among models were narrow. This is not a methodological artifact. It is an

empirical result: expert-perceived governance quality, by itself, does not predict profitability in this sector.

Supplementary Fig. S2 compares model performance across all four metrics.

5.5 Ranking comparison and Spearman correlation

Table 4 compares the TOPSIS governance ranking, the ML-predicted ranking (based on ANN enterprise-level predictions), and the actual ROA ranking. The Spearman rank correlation coefficients quantify the concordance between these rankings.

Table 4: Ranking comparison across methods.

	Actual		**TOPSIS**		**ANN**	
Ent.	**ROA (%)**	**Rank**	CC_i	**Rank**	**Pred. ROA**	**Rank**
E1	17.4	7	0.613	1	23.5	3
E2	37.1	1	0.337	8	22.4	6
E3	17.1	8	0.453	6	23.6	2
E4	23.8	3	0.609	2	20.9	8
E5	26.0	2	0.590	3	22.4	7
E6	21.1	6	0.527	4	22.6	5
E7	23.3	4	0.390	7	23.1	4
E8	22.1	5	0.508	5	24.9	1

- TOPSIS vs. actual ROA: $\rho = -0.238$ ($p = 0.570$) — weak inverse, not significant
- ANN vs. actual ROA: $\rho = -0.714$ ($p = 0.047$) — moderate inverse, significant at the 5% level
- TOPSIS vs. ANN: $\rho = -0.214$ ($p = 0.610$) — weak inverse, not significant

The negative Spearman correlation between TOPSIS and actual ROA ($\rho = -0.238$) confirms the disconnect between perceived governance quality and financial performance. Enterprise E2, perceived as the weakest in governance, has by far the strongest financial returns, while E1, perceived as the best-governed, ranks seventh in profitability. Supplementary Fig. S3 visualizes the three rankings side by side.

5.6 SHAP feature importance analysis

Even when predictive accuracy is poor, SHAP analysis can reveal which governance dimensions carry the strongest statistical signal for financial performance. Table 5 presents the mean absolute SHAP values for both Random Forest and XGBoost (trained on the full dataset), alongside the CRITIC weights for comparison.

Table 5: Feature importance comparison: CRITIC weights vs. SHAP values.

Code	Indicator	RF $\lvert\phi\rvert$	XGB $\lvert\phi\rvert$	CRITIC w_j
C5.1	Employee relations	0.915	1.145	0.080
C5.2	Government relations	0.510	1.036	0.097
C3.2	Innovation investment	0.247	0.710	0.086
C4.1	Internal audit	0.353	0.707	0.103
C1.1	Board composition	0.319	0.678	0.097
C2.2	Audit independence	0.284	0.611	0.106
C3.1	Strategic planning	0.297	0.596	0.130
C2.1	Financial reporting	0.219	0.576	0.095
C4.2	Risk management	0.133	0.502	0.115
C1.2	Independent members	0.146	0.491	0.091

The divergence from the CRITIC weights is stark. Employee relations (C5.1) ranks last in CRITIC weight (0.080) but first in SHAP importance (mean $|\phi| = 1.145$ for XGBoost). Strategic planning (C3.1), the top CRITIC indicator (0.130), drops to seventh in SHAP importance. The pattern points to a conceptual distinction worth emphasizing: CRITIC identifies which indicators most effectively *differentiate* enterprises in expert perception, while SHAP identifies which indicators are most strongly *associated with financial performance*. The two questions turn out to have very different answers. Fig. 3 presents the SHAP summary plot.

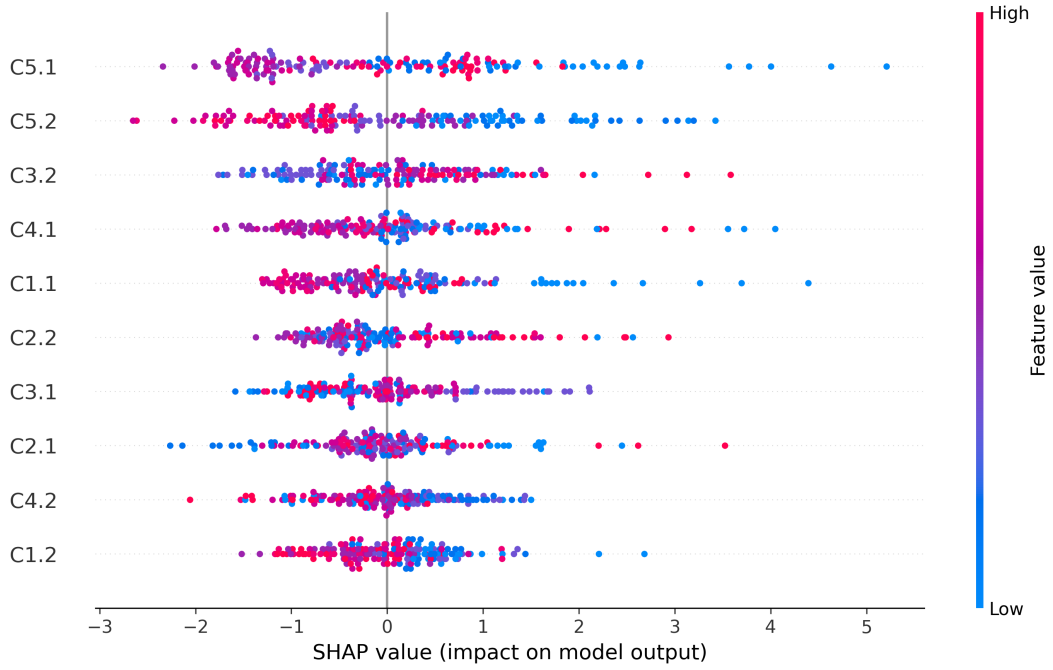


Figure 3: SHAP summary plot (XGBoost). Each dot represents one observation. The horizontal position shows the SHAP value (impact on predicted ROA), and color indicates the feature value (red = high, blue = low).

Supplementary Fig. S4 directly contrasts the CRITIC weights with the SHAP-derived importance (normalized to sum to 1.0). The stakeholder relations dimension (D5) dominates SHAP importance while receiving the least weight under CRITIC, highlighting the conceptual difference between governance discriminability and governance-performance association.

6 Discussion

The empirical results raise questions that go beyond the immediate context of Uzbekistan's construction materials sector. We discuss the main findings in turn, drawing connections to the broader governance literature.

6.1 The governance perception–performance disconnect

The negative Spearman correlation ($\rho = -0.238$) between perceived governance quality and actual ROA ranking is the most arresting result. E2, ranked last in governance perception, posts the highest ROA (37.1%); E1, ranked first, sits seventh in profitability (17.4%). The disconnect, though pronounced here, is not without precedent. [2] found that governance indices do not reliably predict firm performance, and [10] noted that in emerging markets the governance–performance link is moderated by institutional context, ownership structure, and market conditions.

Two factors likely contribute to the pattern in Uzbekistan. Financial performance in the construction materials sector depends heavily on variables outside governance—geographic proximity to infrastructure projects, raw material endowments, production capacity, and access to government procurement contracts. A firm can achieve high ROA through favorable market positioning despite mediocre governance, just as a firm can invest in board restructuring and audit systems that depress short-term profitability while building long-term resilience. In addition, expert perceptions may track enterprise visibility and reputation rather than direct knowledge of internal governance practices, creating a halo effect that favors larger or more prominent firms regardless of their financial returns.

6.2 What differentiates governance perceptions: interpreting the CRITIC weights

Strategic planning (C3.1, $w = 0.130$), risk management (C4.2, $w = 0.115$), and audit independence (C2.2, $w = 0.106$) emerged as the indicators with the greatest discriminatory power. Expert assessments of these three dimensions varied most across the eight enterprises and correlated least with one another, making them the most informative basis for distinguishing governance quality. Employee relations (C5.1, $w = 0.080$) and innovation investment (C3.2, $w = 0.086$), by contrast, drew more uniform ratings, suggesting that experts saw these dimensions as broadly similar across the sector.

The pattern is plausible given the structure of Uzbekistan's construction materials industry. Strategic planning and risk management capabilities depend on ownership form (joint-stock vs. LLC), management professionalism, and access to consulting resources—all of which vary widely across the eight firms. Employee relations and innovation, on the other

hand, are shaped by sector-wide labor market conditions and technology availability that constrain all enterprises similarly.

6.3 What tracks financial performance: the SHAP results

Stakeholder relations indicators—employee relations (C5.1, mean $|\phi| = 1.145$) and government relations (C5.2, mean $|\phi| = 1.036$)—dominated the SHAP importance rankings, standing in sharp contrast to the CRITIC weights that placed strategic management and internal controls at the top. The implication is that the governance dimensions most useful for *telling enterprises apart* are not the same dimensions most closely *tied to profitability*.

Why should stakeholder relations matter more for the bottom line than board structure or strategic planning? In Uzbekistan's transitional business environment, regulatory relationships and labor force management have an outsized operational impact. Constructive government relations—regulatory compliance, access to procurement channels, navigation of licensing requirements—can be decisive for revenue, while effective employee management—retention, motivation, shop-floor efficiency—directly affects costs. Formal governance structures such as board composition or strategic planning documentation, by contrast, may represent necessary institutional scaffolding without translating into short-run financial returns. The finding is consistent with [18], who argued that in emerging markets with institutional voids, relational governance mechanisms often substitute for and outperform formal ones.

6.4 Why governance perceptions do not predict ROA

The negative R^2 values limit the framework's predictive utility, but they constitute a finding in their own right: the relationship between perceived governance quality and financial performance is neither direct nor linear in this sector. Treating governance as the sole determinant of profitability oversimplifies a system in which geography, resource endowments, production capacity, and state procurement contracts all play substantial roles.

A methodological factor compounds the problem. The 160 observations map onto only eight distinct ROA targets, and inter-rater variability in the Likert-scale evaluations introduces noise that attenuates whatever governance-to-performance signal exists. Incorporating additional predictors—enterprise size, age, capital intensity, market share—alongside governance indicators would help future work isolate the marginal contribution of governance quality and likely improve out-of-sample accuracy.

6.5 Practical implications

Even with the imperfect governance–performance link, the framework yields actionable guidance. The CRITIC-weighted Fuzzy-TOPSIS ranking gives managers and regulators a transparent, data-driven map of how governance quality is perceived across the sector—and which enterprises stand to gain most from targeted improvement. SHAP results sharpen the prescription: investing in employee motivation systems and cultivating sound regulatory relationships is likely to pay off more than cosmetic improvements to board composition or the volume of strategic-planning documentation.

For policymakers, the message is that international governance codes—with their emphasis on board independence, audit quality, and disclosure—address necessary but apparently insufficient conditions for financial improvement in this context. Reform programs in Uzbekistan's construction materials sector should complement structural mandates with incentives for relational governance: stakeholder engagement, workforce development, and proactive regulatory dialogue. The weak link between perception-based assessments and financial outcomes also argues for supplementing expert evaluations with operational and financial data, rather than treating governance scorecards as stand-alone performance diagnostics.

6.6 Limitations

Several caveats apply. The sample—eight enterprises, 20 experts—is sufficient for an exploratory sectoral study but constrains both the generalizability of the findings and the statistical power available to the ML models. Because the design is cross-sectional, it captures associations at a single point in time and cannot support causal claims. ROA serves as the sole performance metric; profitability is only one facet of enterprise performance, and alternative measures (Tobin's Q, total factor productivity, or composite indices) could reveal patterns that ROA misses. The governance indicators rest on subjective expert ratings that are susceptible to respondent bias and information asymmetry, and the low Cronbach's α values—expected when heterogeneous constructs are measured across enterprises that differ markedly in size and ownership structure—temper claims about measurement reliability.

7 Conclusions

We developed and empirically tested a hybrid CRITIC–Fuzzy-TOPSIS–ML framework for evaluating corporate governance efficiency in Uzbekistan's construction materials manufacturing sector. Eight major enterprises were assessed using primary data from 20 domain experts and audited financial records.

Three principal findings stand out. First, CRITIC identified strategic planning (C3.1) and risk management (C4.2) as the governance indicators with the greatest discriminatory power, offering an objective, data-driven weighting that avoids the subjective pairwise comparisons required by the AHP. Second, the Fuzzy-TOPSIS governance ranking bore almost no resemblance to actual financial performance: the Spearman correlation between perceived governance quality and ROA was negative and nonsignificant ($\rho = -0.238$, $p = 0.570$). In a transitional economy with limited institutional development, better-perceived governance does not automatically translate into stronger financial returns. Third, SHAP analysis revealed that stakeholder relations—employee relations (C5.1) and government relations (C5.2)—were the governance dimensions most closely tied to profitability, diverging sharply from the CRITIC emphasis on strategic and control dimensions. The gap between what differentiates enterprises in expert perception and what correlates with economic outcomes is, itself, an important empirical result.

The practical upshot is straightforward. Enterprise managers in this sector should invest in employee motivation systems and cultivate constructive regulatory relationships; these relational governance dimensions show the strongest link to the bottom line. Policymakers

drafting governance codes and compliance frameworks should recognize that formal structural reforms—board composition, strategic planning documentation, audit independence—are necessary but insufficient, and should pair structural mandates with incentives for relational governance improvement.

Several avenues for future research follow naturally. A larger sample spanning additional enterprises and sectors would strengthen generalizability and give ML models the statistical power they lacked here. Longitudinal panel data would move the analysis from association to causal inference. Enriching the predictor set with enterprise size, capital structure, and market competition intensity would help disentangle the marginal contribution of governance quality from confounding factors. Replicating the framework in other Central Asian or post-Soviet transitional economies would test whether the governance-perception–performance disconnect and the primacy of relational governance are features of this particular context or broader phenomena.

Ethics declarations

This study was reviewed by the Research Office of Fergana State Technical University and deemed exempt from formal ethics committee approval. The research involved an anonymous expert survey with no collection of sensitive personal data and no involvement of vulnerable populations. All participants were industry professionals and academics who took part voluntarily; completion and return of the questionnaire constituted implied informed consent. Respondents were informed beforehand that their individual identities and enterprise names would remain confidential and that all data would be reported in anonymized form (enterprises coded E1–E8). The study was conducted in accordance with the principles of the Declaration of Helsinki.

Data availability

The aggregated survey data (decision matrix, CRITIC weights, Fuzzy-TOPSIS results, ML performance metrics, and SHAP importance values), the complete analysis code, and the survey questionnaire are provided as Supplementary Files accompanying this paper. Individual survey response sheets are available from the corresponding author on reasonable request, subject to the confidentiality protections described above. Enterprise identities are withheld to protect commercial confidentiality as assured to participants.

Author contributions

S.A.D. and B.A.O. conceived and designed the study. S.A.D., E.A.M., and A.M.K. collected and curated the survey data. B.A.O. and S.I.K. performed the computational analysis. D.A.K. and I.T.Y. contributed to the literature review and discussion. All authors reviewed and approved the final manuscript.

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Competing interests

The authors declare no competing interests.

Additional information

Supplementary information accompanies this paper.

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